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Modeling the Depressive Mind: A Machine Learning Approach to Deciphering Beck's Cognitive Triad

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Abstract. Mental and cognitive well-being is of paramount significance for human beings. Consequently, the early detection of issues that may culminate in conditions such as depression holds great importance in averting adverse outcomes for individuals. Depression, a prevalent mental health disorder, can severely impact an individual's quality of life. Timely identification and intervention are critical to prevent its progression. Our research delves into the application of Machine Learning (ML) techniques to potentially facilitate the early recognition of depressive tendencies. By leveraging the cognitive triad theory, which encapsulates negative self-perception, a pessimistic outlook on the world, and a bleak vision of the future, we aim to develop predictive models that can assist in identifying individuals at risk. In this regard, we selected The Cognitive Triad Dataset, which takes into account six different categories that encapsulate negative and positive postures about three different contexts: self context, future context and world context. Our proposal achieved great performance, by relying on a strict preprocessing analysis, which led to the models obtaining an accuracy value of 0.96 when classifying aspect contexts; whereas a value of 0.83 in accuracy was achieved under the aspect-sentiment paradigm.

Keywords: Cognitive triad inventory, depression detection, machine learning, classification, logistic regression, support vector machine, SVM.

1 Introduction

Depression is a potentially fatal mental disorder and is estimated to affect 3.8% of the world's population according to World Health Organization (WHO)[1]. It has devastating effects on brain health as the dynamic state of the cognitive, emotional and mental domains, affecting the integrity of the structure and functionality of the brain [2, 3]. For this reason, it is important to identify factors that can help prevent depressive symptoms and serve as markers of some type of permanent brain damage [7, 8]. Cognitive therapy based on Beck's Cognitive Triad has become an effective tool for treating depression by helping people identify, challenge and change their negative thought patterns.

[1] www.who.int/es/news-room/fact-sheets/detail/depression

Table 1. Setup and results for set 1, subtask 1 (macro avg).

Text feature	Model	Parameters	Accuracy	Precision	Recall	F1-score
Preprocessed	LR	`penalty="l2"`	**0.96**	**0.96**	**0.96**	**0.96**
	DT	`criterion="gini"`	0.93	0.93	0.93	0.93
	RF	`n_estimators=100`	0.95	0.95	0.95	0.95
	SVM	`kernel="rbf"`	**0.96**	**0.96**	**0.96**	**0.96**
No stopwords	LR	`penalty="l2"`	0.69	0.69	0.69	0.69
	DT	`criterion="gini"`	0.64	0.64	0.64	0.64
	RF	`n_estimators=100`	0.68	0.68	0.68	0.68
	SVM	`kernel="rbf"`	0.70	0.70	0.70	0.70
Lemmatized	LR	`penalty="l2"`	0.95	0.95	0.95	0.95
	DT	`criterion="gini"`	0.93	0.93	0.93	0.93
	RF	`n_estimators=100`	0.95	0.95	0.95	0.95
	SVM	`kernel="rbf"`	0.95	0.95	0.95	0.95

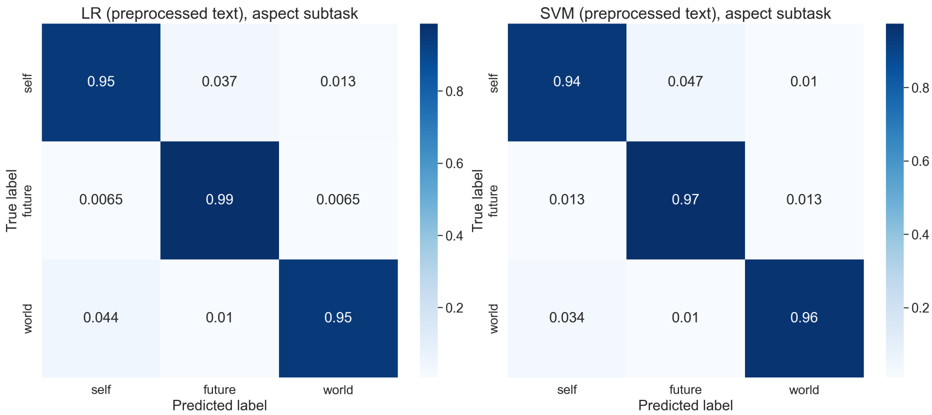
By challenging and replacing these cognitive distortions, people can experience a reduction in depressive symptoms and improve their emotional well-being. Beck's Cognitive Triad is a central concept of the cognitive theory of depression developed by Aaron T. Beck [1]. This theory is based on the idea that people suffering from depression tend to have distorted and negative thought patterns that influence their emotional state. Beck's triad refers to three interrelated components of the following thought patterns:

– **Negative view of self (self-concept)**: People experiencing depression often have a negative perception of themselves. They feel that they are incompetent, unworthy or inadequate in various aspects of their lives. This negative self-perception can affect their self-esteem and self-confidence.

– **Negative view of the world (external world)**: Depressed people tend to view the world around them in a pessimistic and negative way. They may perceive their environment as hostile, threatening, or overwhelming. This negative view of the world can lead to feelings of hopelessness and lack of control over their environment.

– **Negative view of the future (future)**: Depressed people often have a pessimistic expectation about the future. They may anticipate difficulties and failures rather than positive possibilities. This negative outlook on the future contributes to feelings of hopelessness and apathy.

It stems from his approach to cognitive therapy of depression, which focuses on identifying and changing the negative and distorted thought patterns that contribute to the depressive experience. Beck proposed that these negative thought patterns are unrealistic and inaccurate, and that they influence a person's emotional state by maintaining and amplifying depression.



(a) LR (preprocessed text) (b) SVM (preprocessed text)

Fig. 1. Confusion matrices for set 1, subtask 1 best models.

It is of great importance because it provides a profound understanding of how thought patterns can influence a person's emotional state and contribute to depression. This theory helped change the way depression is approached and treated by focusing on the active role that thoughts and beliefs play in the depressive experience. Our approach is described in the following sections. This work is structured as follows.

In Section 2 a brief description of the related works in depression detection is given. In Section 3, the description of the datasets, the preprocessing, and feature extraction methods accompanied by the classification models implemented is given. Then, in Section 4 we describe the setup for the experiments and the results obtained after the submission of our predictions. Finally, in Section 5 we discuss our results and some ideas about how to improve them for future work.

2 State of the Art

Jere et al. [6], presented a dataset for the purpose of modeling Beck's Cognitive Triad (CTD) to model subjective symptoms of depression, such as negative view of self, future, and world. CTD is composed of $5,886$ messages, which are divided into six categories: self-positive (spos), world-positive (wpos), future-positive (fpos), self-negative (sneg), world-negative (wneg), and future-negative (fneg). This set was evaluated in two subtasks: aspect detection and aspect-specific sentiment classification. The main purpose of creating the dataset is to aid the understanding of Beck's Cognitive Triad Inventory (CTI) in people's social network postings.

Jere and Patil [5], use their previously created dataset and propose the following classical machine learning models: Decision Tree (DT), Random Forest (RF), Nayve Bayes (NB) and SVMs. They also implemented the following deep learning models: Graph Neural Networks (GNN), Long Short-Term Memory (LSTM), Bilateral Long Short-Term Memory (BiLSTM) and a Recurrent Neural Network (RNN). Their best model for aspect-based sentiment classification was the single-layer RNN, with a precision and F1-score of 0.857 and 0.858 respectively.

Table 2. Setup and results for set 1, subtask 2 (macro avg).

Text features	Model	Parameters	Accuracy	Precision	Recall	F1-score
Preprocessed	LR	`penalty= "l2"`	0.83	0.83	0.83	0.83
	DT	`criterion="gini"`	0.77	0.77	0.77	0.77
	RF	`n_estimators=100`	0.80	0.80	0.80	0.80
	SVM	`kernel="rbf"`	**0.85**	**0.85**	**0.85**	**0.85**
No stopwords	LR	`penalty="l2"`	0.76	0.76	0.76	0.76
	DT	`criterion="gini"`	0.68	0.68	0.68	0.68
	RF	`n_estimators=100`	0.73	0.73	0.73	0.73
	SVM	`kernel="rbf"`	0.76	0.76	0.76	0.76
Lemmatized	LR	`penalty="l2"`	0.82	0.82	0.82	0.82
	DT	`criterion="gini"`	0.76	0.76	0.76	0.76
	RF	`n_estimators=100`	0.80	0.80	0.80	0.80
	SVM	`kernel="rbf"`	**0.85**	**0.85**	**0.85**	**0.85**

For the sentiment recognition subtask, they obtained an accuracy and F1-score of 0.89 and 0.892 respectively with a multilayer RNN model. Finally, for aspect detection they obtained an accuracy and F1-score 0.957 and 0.956 respectively and again with a multilayer RNN. Gonzalez-Gomez et al. [4], analyzed data from two separate samples to assess associations between loneliness, social adjustment, depressive symptoms, and their neural correlates.

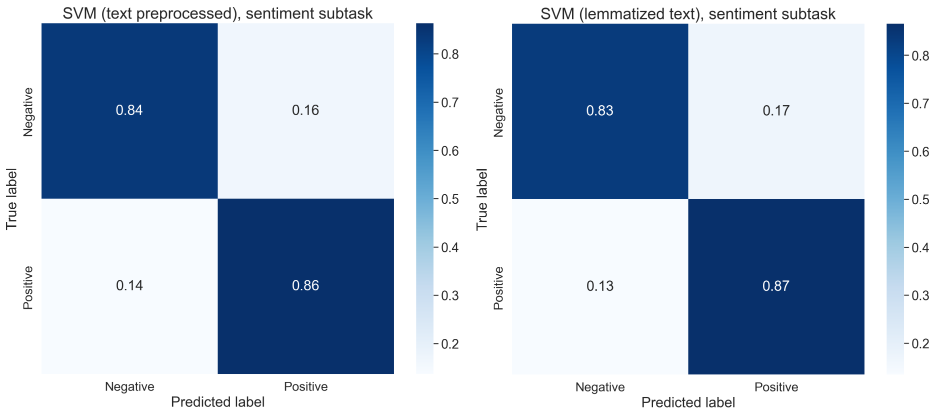
This was achieved by contacting study participants by telephone or social networks to complete various tapping scales on depressive symptomatology, loneliness and social adjustment and these results were assessed with the CTI and the University of California (UCLA) Loneliness Scale and found that after controlling for age, gender, and years of education only loneliness emerged as a significant predictor of depressive symptomatology.

3 Methodology

In this paper we will make use of the dataset collected by Jere et al. [6], in which we will perform an approach with machine learning models such as: Support Vector Machines, Logistic Regression, Decision Trees and Random Forest with different configurations. We will also make some adjustments to the documents of the original dataset by preprocessing them in order to obtain a better extraction of features for our models. Our final goal is to be able to compare our approach with the existing state-of-the-art results, we will perform the same subtasks that the state of the art has used to solve this problem, and we will also use the same evaluation metrics.

3.1 Models

Support Vector Machine (SVM). They are a supervised learning algorithm used for both classification and regression problems. An SVM searches for a hyperplane that best separates two different classes in the feature space.



(a) SVM (preprocessed text)　　(b) SVM (lemmatized text)

Fig. 2. Confusion matrices for set 1, subtask 2 best models.

Table 3. Setup and results for set 2, subtask 1 (macro avg).

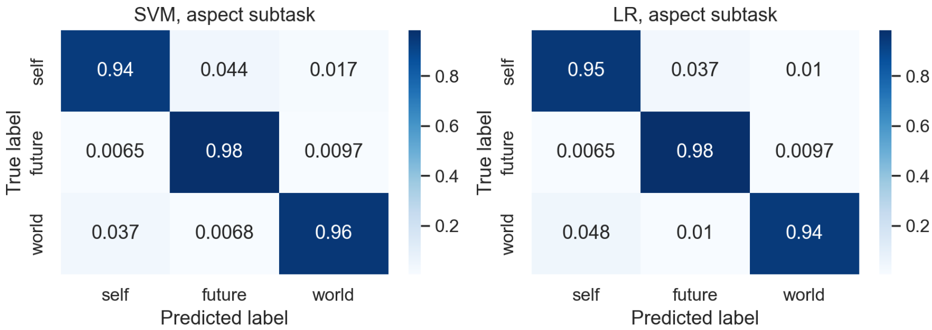
Model	Parameters	Accuracy	Precision	Recall	F1-score
SVM	`kernel= "linear"`	0.96	0.96	0.96	0.96
LR	–	0.96	0.96	0.96	0.96

The hyperplane is a geometric entity that is used to classify points into different categories. If the classes are not linearly separable in the original space, SVMs can use mathematical tricks to map the data to a higher dimensional space where they are linearly separable.

Logistic Regression (LR). It is a supervised learning algorithm used for classification and probability estimation in binary (two-class) or multi-class (more than two classes) problems. Logistic regression models the probability that an instance belongs to a particular class and uses the logistic function (also known as sigmoid function) to transform a linear combination of features into a value between 0 and 1, which is interpreted as the probability. Despite its name, it is mainly used for classification tasks rather than regression.

Decision Trees (DT). These are supervised learning algorithms used for classification and regression problems. They operate by recursively partitioning the feature space into smaller, more homogeneous subsets, with the objective of making decisions based on the hierarchical structure of the tree. At each node of the tree, a feature and a threshold value are selected to split the data into two branches (subsets) based on that feature. The selection of the splitting feature is made based on some criterion, such as information gain in the case of classification or variance reduction in the case of regression.

Random Forest (RF). They are a supervised learning algorithm used primarily for classification and regression tasks. They are a combination of multiple decision trees and are noted for their ability to handle both numerical and categorical data, as well as their ability to avoid overfitting and generate accurate predictions.



(a) SVM (b) LR

Fig. 3. Confusion matrices for set 2, subtask 1 best models.

Table 4. Setup and results for set 2, subtask 2 (macro avg).

Model	Parameters	Accuracy	Precision	Recall	F1-score
SVM	`kernel= "linear"`	0.85	0.86	0.85	0.85
SVM	`kernel= "rbf"`	**0.86**	**0.86**	**0.86**	**0.86**
LR	–	0.84	0.84	0.84	0.84

3.2 Text Preprocessing

Although the documents in the selected dataset are quite readable, there are some improvements that can be made to the text in order to improve the features that our machine learning model will be trained on. These enhancements include:

– **Line breaks**: All the line breaks were removed to obtain a single plain text.

– **Lowercase**: All the uppercase letters turned to lowercase.

– **Apostrophes**: All of them were removed.

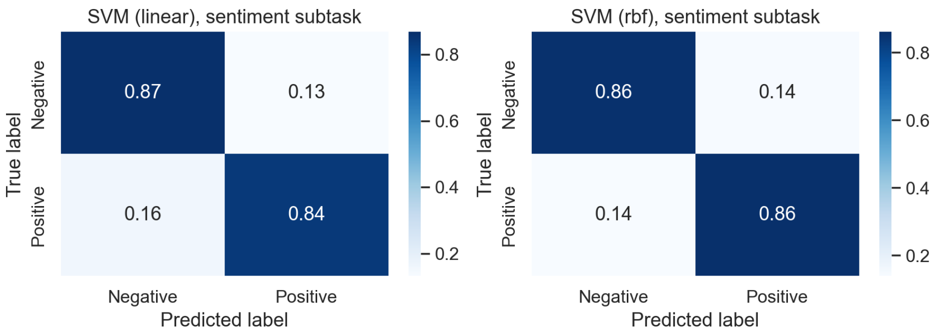
– **Punctuation**: The characters used to punctuate the text (e.g., `. : , ;`) were removed.

– **Repeated characters**: When a word contains a character that repeats more than twice, the characters were trimmed into two repetitions (e.g., hellooooo → helloo).

– **Alphanumeric words**: The words composed by alphabetic and numerical characters like in leet speaking (e.g., h3ll0) were removed.

3.3 Feature Extraction

Bag of words. This model is a simplified representation of a text, where the bag represents the set of all words contained in a document collection. A single document is represented as a vector, where each dimension represents a word from the vocabulary obtained from the document collection and how many times the word appeared in a single document (TF).



(a) SVM (linear) (b) SVM (rbf)

Fig. 4. Confusion matrices for set 2, subtask 2 best models.

Table 5. Results for set 2, aspect-sentiment CTD task (macro avg).

Model	Accuracy	Precision	Recall	F1-score
Aspect-sentiment	0.83	0.83	0.83	0.82

TF·IDF. This method makes use of the term frequency (TF), and the inverse document frequency (IDF). For the TF calculation, a bag of words is generated with the vocabulary of the set of all documents that are to be analyzed, then the total number of occurrences of the word is obtained. IDF is calculated as the logarithm of the quotient of the number of documents in which the analyzed word appears and the number of documents in which it appears in the analyzed set. Finally, the product between TF and IDF is performed for each of the words in the analyzed text, generating a vector of characteristics.

4 Experiments and Results

The solution proposed in this paper consists of two different approaches. The aspect-sentiment based classification and the multi-class scenario. These approaches are further described in their corresponding section.

4.1 Aspect-Sentiment Approach

For this approach, the main classification task was divided into two subtasks, the first one was the aspect identification subtask. For this task, we trained a model to detect whether the text was describing the author's thoughts about themselves (self), about future scenarios (future) or about the exterior (world). The second subtask was to detect the sentiment reflected by the author's in the text, whether they were positive or negative. For both sets of experiments, the dataset was redistributed to adequate it for the subtasks aim. The redistribution is described below.

Subtask 1. Aspect identification. A ternary dataset was generated, the class division was:

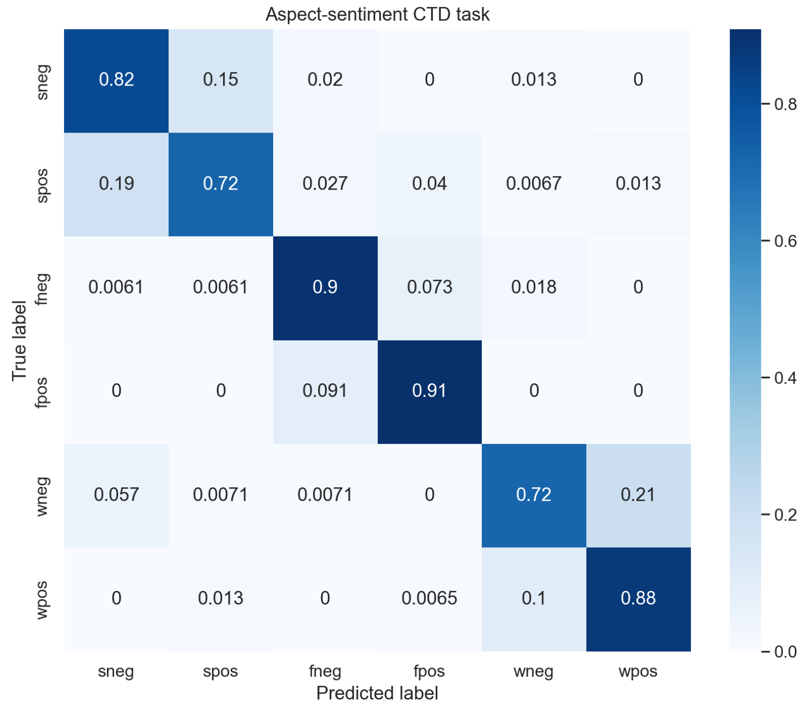


Fig. 5. Confusion matrix for set 2, aspect-sentiment CTD task.

– {self-negative, self-positive} → {self}

– {future-negative, future-positive} → {future}

– {world-negative, world-positive} → {world}

Subtask 2. Sentiment classification. For this subtask, the redistribution of the classes of the dataset was performed as follows:

– {self-negative, future-negative, world-negative} → {negative}

– {self-positive, future-positive, world-positive} → {positive}

Experiments, set 1. For this first phase of experimentation, we will perform experiments with the following machine learning models: LR, RF, DT and SVMs. The configuration to be used for these experiments will be the following: as tokenizer, we will use TF·IDF, with a minimum word occurrence frequency of 3 and a range of n-grams of 3. In order that these experiments can be replicated, it should be mentioned that the respective models of the `scikit-learn` library for Python with seed 42 were used.

Subtask 1. In the table 1 it can be seen that the best results with this configuration are LR and SVM with the specific feature that the text was preprocessed. We can also observe the behavior of the best models through their respective confusion matrices in the figure 1.

Table 6. Setup and results for set 1, multi-class (macro avg).

Text features	Model	Parameters	Accuracy	Precision	Recall	F1-score
Preprocessed	LR	`penalty="l2"`	**0.79**	**0.80**	**0.79**	**0.79**
	DT	`criterion="gini"`	0.69	0.69	0.69	0.69
	RF	`n_estimators=100`	0.76	0.76	0.76	0.75
	SVM	`kernel="rbf"`	0.79	0.79	0.78	0.78
No stopwords	LR	`penalty="l2"`	0.56	0.56	0.56	0.56
	DT	`criterion="gini"`	0.47	0.47	0.47	0.47
	RF	`n_estimators=100`	0.54	0.54	0.54	0.53
	SVM	`kernel="rbf"`	0.58	0.58	0.58	0.58
Lemmatized	LR	`penalty="l2"`	**0.79**	**0.79**	**0.79**	**0.79**
	DT	`criterion="gini"`	0.69	0.69	0.69	0.69
	RF	`n_estimators=100`	0.75	0.75	0.75	0.75
	SVM	`kernel="rbf"`	**0.79**	**0.79**	**0.79**	**0.79**

Table 7. Setup and results for set 2, multi-class ensemble model (macro avg).

Model	Class	Kernel	Accuracy	Precision	Recall	F1-score
svm_sneg	self-negative	linear	0.89	0.89	0.89	0.89
svm_spos	self-positive	rbf	0.85	0.85	0.85	0.85
svm_fneg	future-negative	linear	0.90	0.90	0.90	0.90
svm_fpos	future-positive	rbf	0.90	0.90	0.90	0.90
svm_wneg	world-negative	rbf	0.85	0.85	0.85	0.85
svm_wpos	world-positive	linear	0.93	0.93	0.93	0.93

Subtask 2. The results for this subtask can be seen in the table 2. For this second subtask, there are two models competing to be the best, however, both models are SVMs, with the difference being the treatment given to the text, one model was with preprocessed text and the other with lemmatized text. The confusion matrices for these models are shown in figure 2.

Experiments, set 2. After the first stage of experiments in the aspect-sentiment approach, we performed a second trial to improve the performance of those obtained in the first set.

Subtask 1. Once the classes were redistributed, the preprocessed texts were tokenized. The tokenizer and its parameters are the following: as tokenizer, we will use TF·IDF, with a minimum word occurrence frequency of 2, maximum document frequency of 0.9 and a range of n-grams of 2. Then, several models were trained and evaluated to test their performance.

After the evaluation, two models draw, obtaining the best performance. To make the experiments replicable, the seed for the random generations were set to 77. The best models setup and results are described in Table 3, their confusion matrices are shown in Figure 3.

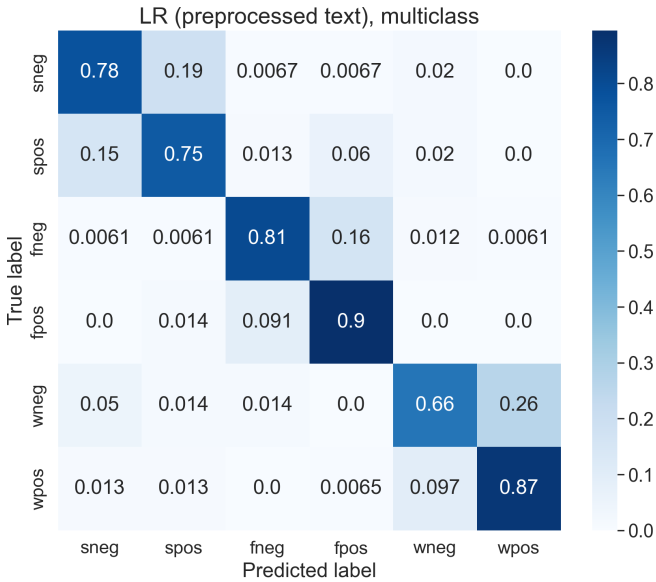


Fig. 6. Confusion matrix for set 1, LR (preprocessed text) multi-class.

Table 8. Results for set 2, multi-class SVM ensemble (macro avg).

Model	Accuracy	Precision	Recall	F1-score
SVM ensemble	0.77	0.77	0.77	0.77

Subtask 2. As in the aspect identification subtask, preprocessed texts were tokenized. The tokenizer ant its parameters are the following: as tokenizer, we will use TF·IDF, with a minimum word occurrence frequency of 2, maximum document frequency of 0.17 and a range of n-grams of 2.

In total, three models were trained and evaluated for this subtask, the model configuration and their results are described in Table 4, their confusion matrices are shown in Figure 4. Figure 4a corresponds to the SVM with linear kernel, Figure 4b shows the results for the SVM with `rbf` kernel.

Aspect-sentiment classification. Once both subtasks were completed, the cognitive triad of depression (CTD) classification task was performed. To accomplish it, the best models from the subtasks 1 and 2 were selected and put together:

– Subtask 1: SVM with linear kernel.

– Subtask 2: SVM with rbf kernel.

The results for this classification stage are shown in Table 5, and the confusion matrix is shown in Figure 5. This set of experiments revealed interesting things about the features and the models. For the aspect identification subtask, words with high frequency (those that are present in 90% of the documents or less) and low frequency ones (those repeated in at least two documents) are relevant for the model performance,

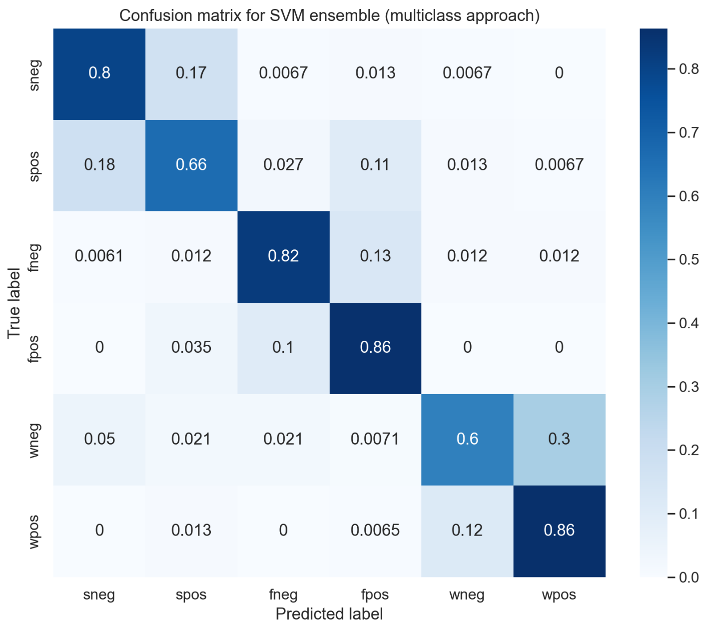


Fig. 7. Confusion matrix for set 2, multi-class SVM ensemble.

Table 9. Comparison, aspect identification task.

Author	Model	Accuracy	Precision	Recall	F1-score
Jere et al. (2021) [6]	SVM	0.77	0.78	0.77	0.78
	RNN-C	**0.96**	**0.97**	0.95	**0.96**
Jere and Patil (2022) [5]	SVM	0.77	0.77	0.76	0.77
	LSTM	0.90	0.90	0.90	0.90
	RNN-AC	**0.96**	0.96	**0.96**	**0.96**
Our proposal	SVM	0.96	0.96	0.96	0.96

but for the sentiment classification subtask, the most frequent words are irrelevant (those words repeated in more than the 17% of the documents are ignored) and even with that feature reduction, the models were able to obtain promising results. For both subtasks, the best models were SVMs that in the CTD classification task performed very good.

4.2 Multi-Class Approach

Experiments, set 1. The first experimentation phase for this subtask was based on the first experimentation phase for subtask 1. Thus, the models used as well as their corresponding configurations were exactly the same, the only difference will be that this approach will be a multi-class approach. The results of this phase are shown in the table 6, where we obtained three models with similar results: RL with preprocessed text, LR and SVM with lemmatized text.

Table 10. Comparison, sentiment classification task.

Author	Model	Accuracy	Precision	Recall	F1-score
Jere et al. (2021) [6]	SVM	0.78	0.79	0.78	0.79
	RNN-C	**0.89**	**0.90**	0.88	**0.89**
Jere and Patil (2022) [5]	SVM	0.77	0.78	0.77	0.77
	LSTM	0.87	0.87	0.87	0.87
	RNN-AC	**0.89**	0.89	**0.89**	**0.89**
Our proposal	SVM	0.86	0.86	0.86	0.86

Table 11. Comparison, aspect-sentiment CTD classification task.

Author	Model	Accuracy	Precision	Recall	F1-score
Jere et al. (2021) [6]	SVM	0.61	0.62	0.60	0.61
	RNN-C	**0.86**	**0.86**	**0.86**	**0.86**
Jere and Patil (2022) [5]	SVM	0.61	0.62	0.60	0.61
	LSTM	0.82	0.82	0.82	0.82
	RNN-AC	**0.86**	**0.86**	**0.86**	**0.86**
Our proposals	Aspect-sentiment	0.83	0.83	0.83	0.82
	LR (preprocessed text)	0.79	0.80	0.79	0.79
	SVM-ensemble	0.77	0.77	0.77	0.77

RL with the preprocessed text was chosen as the best model of all since LR with the lemmatized text at the end of the experimentation did not end up converging with the predetermined number of iterations, on the other hand the SVM model with the lemmatized text has a lower precision value. The confusion matrix for the best model is shown in Figure 6.

Experiments, set 2. After the first stage of experiments in the multi-class scenario, we performed a second experiment that consisted of a model ensemble. The ensemble consists of six SVMs trained to identify each of the six classes. To put the ensemble together, we first trained each of the models in a binary classification scenario.

To achieve this, the main dataset was divided into subsets that contained all the samples of the class to train, then we balanced the subsets with random samples of data of the other five classes in the same proportion (approximately 20% of the size of the class to balance), obtaining six subsets to train and test the models of the ensemble.

For each of the models a different tokenizer was fitted to tokenize the preprocessed text, the parameters used to fit the tokenizers were the same, a TF·IDF vectorizer from `scikit-learn` with an N-gram range of unigrams and bigrams, trough experimentation, we realized that unique words (those that appear just in one document) does not affect the performance of the models and that those words with high frequencies neither.

The final setup is the following: as tokenizer, we will use TF·IDF, with a minimum word occurrence frequency of 2, maximum document frequency of 0.25 and a range of n-grams of 2. The setup and results for each of the ensemble models is described in Table 7. To make the experiments replicable, the random generation seeds were set to 77.

Finally, when the models were put all together to build the ensemble, the results shown in Table 8 were obtained. The confusion matrix for the SVM ensemble model is displayed in Figure 7. The results obtained from this approach revealed that the multi-class approach is promising, further experimentation is required to outperform the results obtained from the aspect-sentiment approach.

4.3 Comparison with the State of the Art

Here, a comparison between the results obtained from our proposal and those from the state of the art is provided. The results obtained from the aspect identification tasks are shown in Table 9, those obtained from the sentiment classification task in Table 10, and the CTD classification are shown in Table 11. The comparison was made between ML and DL models on purpose, from the tables above, it can be inferred that although our ML proposals did not outperform the DL models are very competitive, overpassing the ML models proposed in the literature, and even reaching the DL models performance in some cases like the aspect identification task. The multi-class approach got some very good results, providing a new baseline for future proposals in this approach.

5 Discussion and Future Work

The results obtained in this paper suggest that ML algorithms are suitable for classifying text sequences based on two different characteristics that are simultaneously present under the Beck's Cognitive Triad, i.e., aspect analysis, whether it is self, world or future focused; and sentiment analysis, to determine if what was said is positive or negative with respect to the corresponding aspect. In this regard, our aspect-sentiment approach, which consists of two models, each one of them responsible of classifying either aspect or sentiments, to subsequently conjugate their results to deliver a final label, showed to be the most appropriate proposal for the task in question.

Additionally, we consider that these results are a consequence of the preprocessing pipeline applied to the data, which was based on our observations on the tasks after an in depth analysis. Therefore, we believe that data processing, even though lately, has received little to no attention, is still a procedure of vital importance, since it allows algorithms to learn on specific properties of the input data.

Furthermore, a new approach to this problem, the multi-class approach, was proposed. This approach trains directly on the corpus, without the need to divide the main task into subtasks. Despite this strategy, the proposed models showed good performance, outperforming those ML models proposed in the literature, setting the baseline for future attempts in this approach.

Although in this paper we focused exclusively on traditional ML algorithms, due to the evidence in the literature, we consider that further research needs to be carried on taking into account Deep Learning (DL) architectures, such as Recurrent and Convolutional Neural Networks; furthermore, the preprocessing stages need to keep playing an important role, since not only linguistic features need to be considered, but under the DL paradigm, the type of data a given architecture is prone to is also of great relevance for the model's performance.

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